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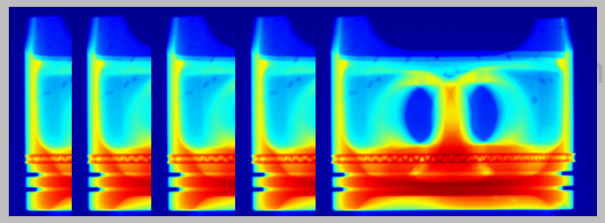

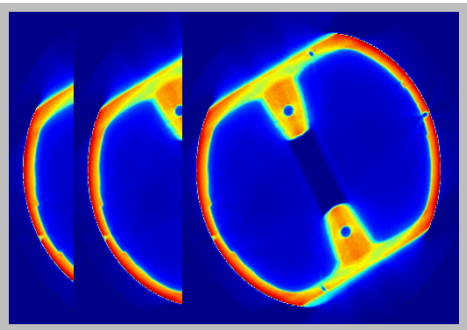

Irregular Big Data Computed Tomography on Multiple Graphics Processors Improves Energy-Efficiency Metrics for Industrial Applications

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Hispanic Engineers National Achievement Awards Conference 2014

October 2014

U.S. DEPARTMENT OF ENERGY

NNSA National Nuclear Security Administration

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Computed Tomography

- Computed Tomography (CT) is an indirect 3D imaging technique.
- Input: Set of X-ray images acquired about a center of rotation.
- Output: Three-dimensional approximation of internal and external structure
- Reconstruction: Convolution- Backprojection Algorithm (Feldkamp-Davis-Kress)
- Geometry and Configuration of CT System determines magnification
- Reconstruction algorithm is $O(n^4)$

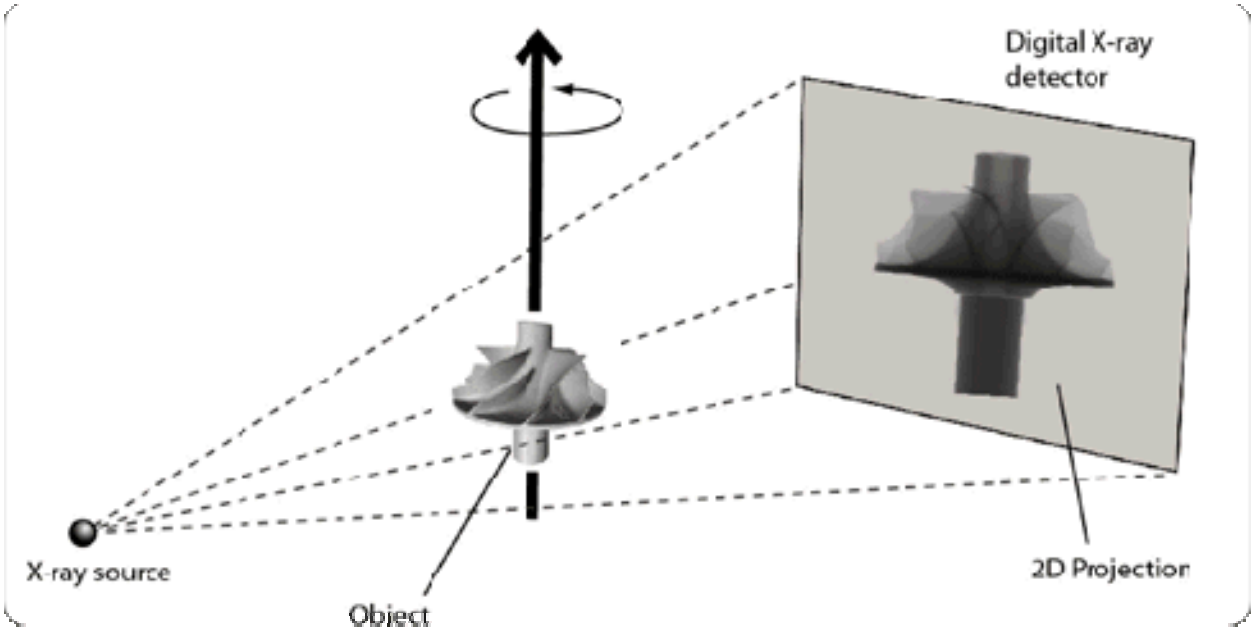

Image Source: http://www.xviewct.com/assets/images/how-ct-works.gif

GPU

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- Graphics Processing Units are coprocessors that handle image manipulation and now are being used for general purpose computing.
- Capable of Teraflops!
- This massive computational capability of GPUs can be harnessed for many applications.
  - Parallel computing environment
  - Fast dedicated memory
  - Fast Cache
- CT Reconstruction from projection images requires many arithmetic and trigonometric operations for every volumetric pixel (voxel).

CT on GPUs

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- "Porting" CT reconstruction on GPUs has shown major bottlenecks.
  - Usually not an issue with medical datasets.
  - Memory uploads/downloads to device (GPU).
  - What ratio of x-ray data to volume should be allocated?
- Traditional CPU-based code reconstructed one slice at a time
  - Predicable memory access even when multi-threaded.
- GPU-based reconstruction
  - Massively multithreaded environment creates scattered memory reads if large x-ray data is utilized.
  - Scattered Memory reads severely hinders performance!
  - Suddenly reconstruction becomes an Irregular Problem!

Approach

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- Maximize resources by blocking x-ray data and sub-volumes.
  - Not necessarily a new idea…
- Counter Intuitive: *Maximize* x-ray data uploads to device!
  - Partition x-ray images and batch small x-ray image subsets
- Volume: Use most GPU memory for direct volume storage.
- Utilize GPU-Specific Hardware/Features
  - Massive parallelism
  - Texture memory/Texture Cache
  - Constant Memory
  - Data prefetch to pinned memory for fast upload
- Dynamic Task Partitioning
  - Ensures only relevant data is fetched and uploaded to the device

GPU Cache Hierarchy

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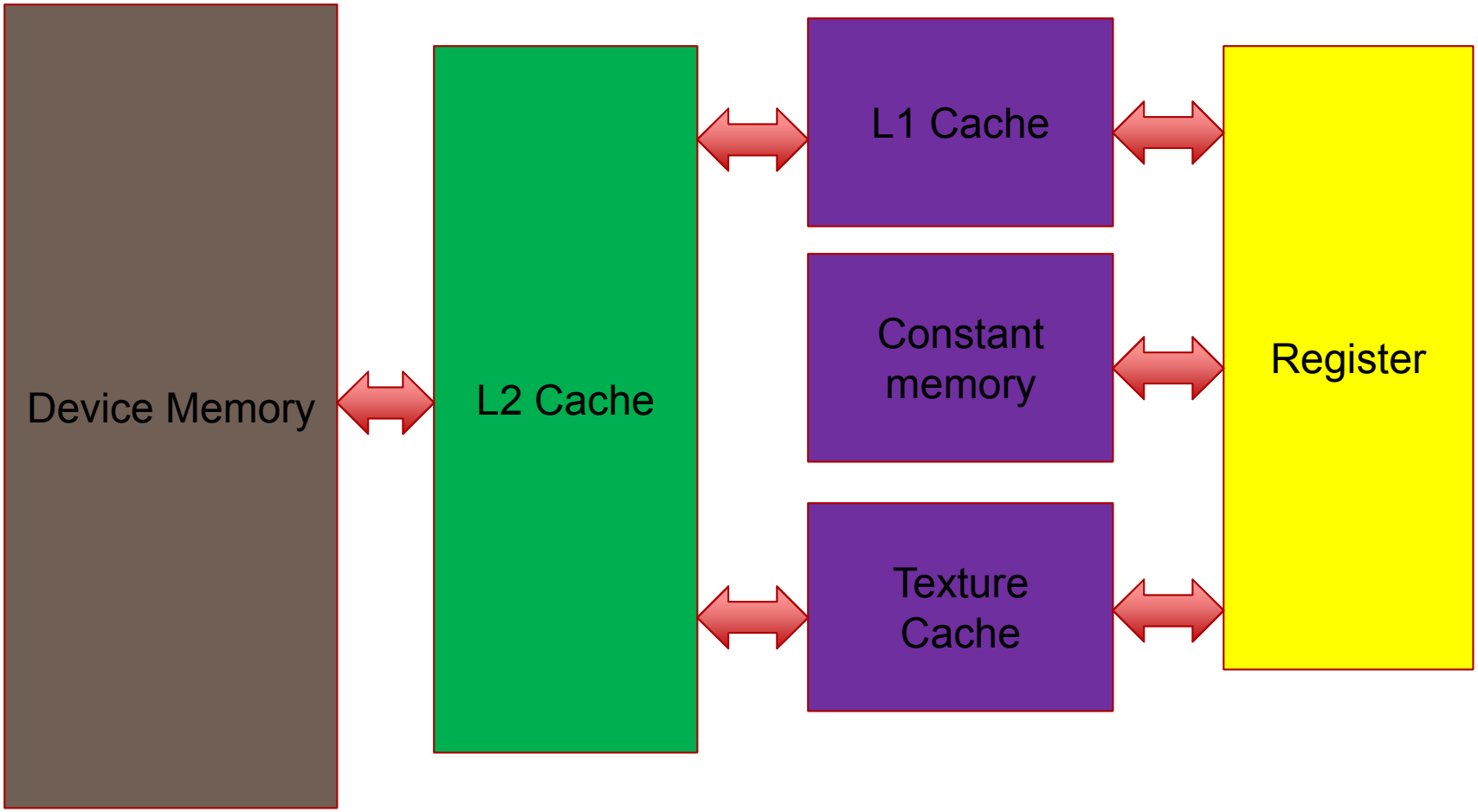

Implementation

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- CUDA Programming environment and C++
- Minimum requirements
  - Fermi-based architecture or newer
  - 1 GB device memory
  - At least one x-ray sub image and one image plane must fit together on device
- Allows for 1 – 8 GPUs per node
- Dynamic Partitioning determined by *slice-to-texture ratio* (*STR*)
- STR may not always be satisfied:
  - Resource maximization vs. Awkward task size
  - Reconstruction size – Too large or small?
  - Tail-end reconstruction

Dynamic GPU Tasking

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- For a given subvolume the amount of x-ray data necessary varies
  - Due to the geometry of the system.
  - Taken into account with STR to determine memory data allocation on device.
  - Typically, reconstruction along center slices require less data.

- Using OpenMP 2.0, a CPU thread controls one GPU in the system
  - Each GPU will usually be reconstructing sub-volumes of varying size
  - Load balancing difficult if subvolume is fixed for all GPUs

- No synchronization necessary for CPU threads while algorithm is executing.

- No synchronization necessary between GPU threads either.

- One atomic operation to update reconstruction progress and determine next subvolume to reconstruct.

FDK Kernel Layout

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- **Input:** X-ray data, index, and size, subvolume data, index, and size, system geometry
- Get thread *ID* and voxel positions $p_1, \ldots, p_s$ based on *ID*
  - **if** Thread *ID* position within ROI **then**
    - **for** Every slice *j* in slice block **do**
      - Set register value to zero
      - **for** Every image *i* in image subset **do**
        - » Determine texture interpolation coordinate in image *i*
        - » Update register value with texture fetch and scaling
      - **end for**
      - Update voxel p_j in global memory with register value
    - **End for**
  - **End if**

Evaluation

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- Supermicro workstation
  - Dual Octo-core Intel Xeon E-2687W @ 3.1 GHz w/ hyper threading
  - 512 GB RAM
  - 4 PCI-E 2.0 x16 slots
- 2 NVidia S2090 Devices
  - 4 Tesla M2090 GPUs each (8 total)
  - Connected via 4 PCI-E host interface cards
- M2090
  - 6 GB GDDR5 memory apiece
  - 16 streaming multiprocessors (SM)
  - 768 KB L2 Cache (load, store, and texture operations)
  - 32 Compute cores per SM
  - 48 KB L1 Memory (explicitly set, shared memory not used)
  - 8 KB Constant Memory and Texture Cache
- Two datasets tested
  - 64 Gigavoxels
  - 1 Teravoxel

Results: Throughput 64 GV/ 1 GPU

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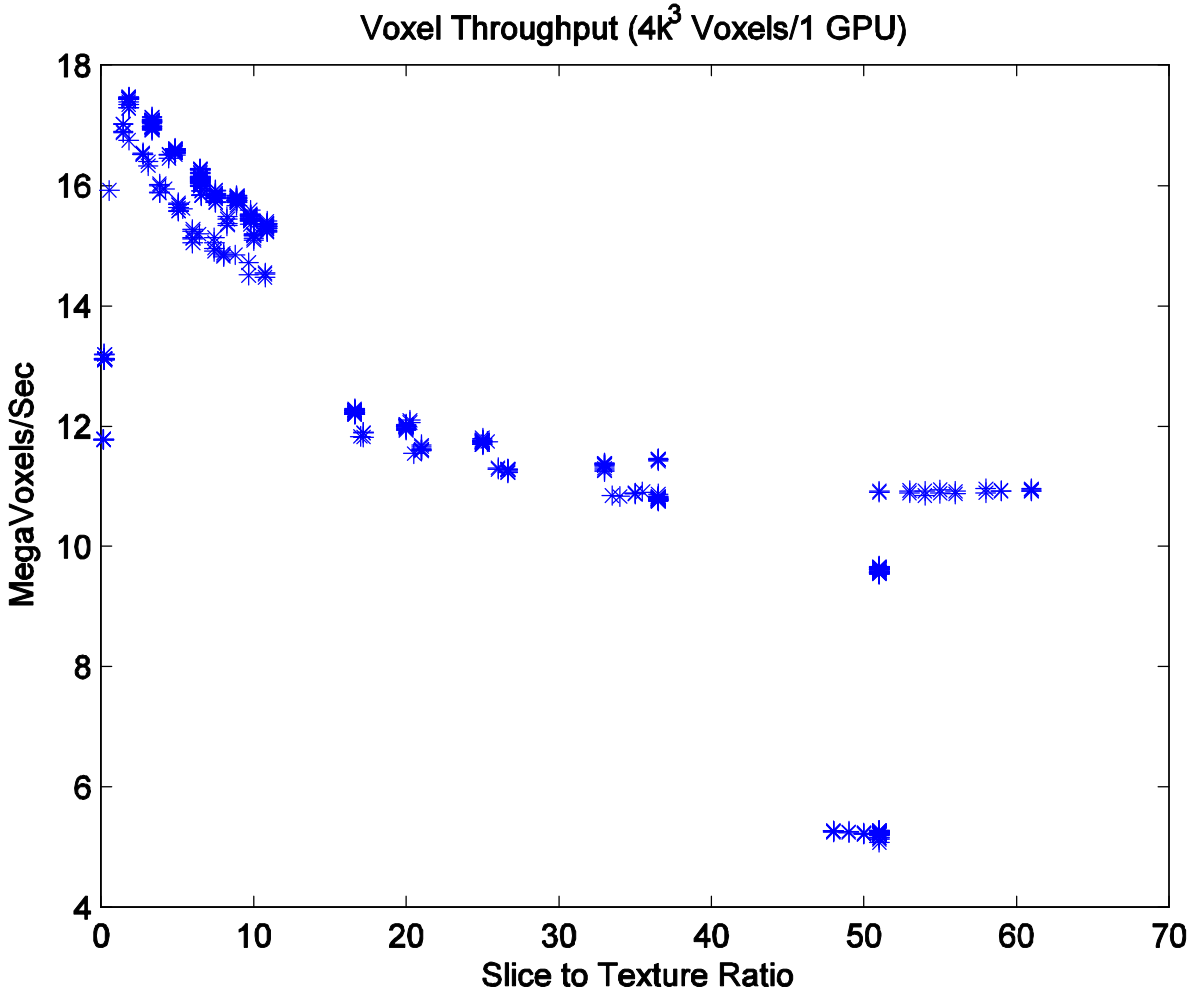

Results: Throughput 64 GV/ 8 GPUs

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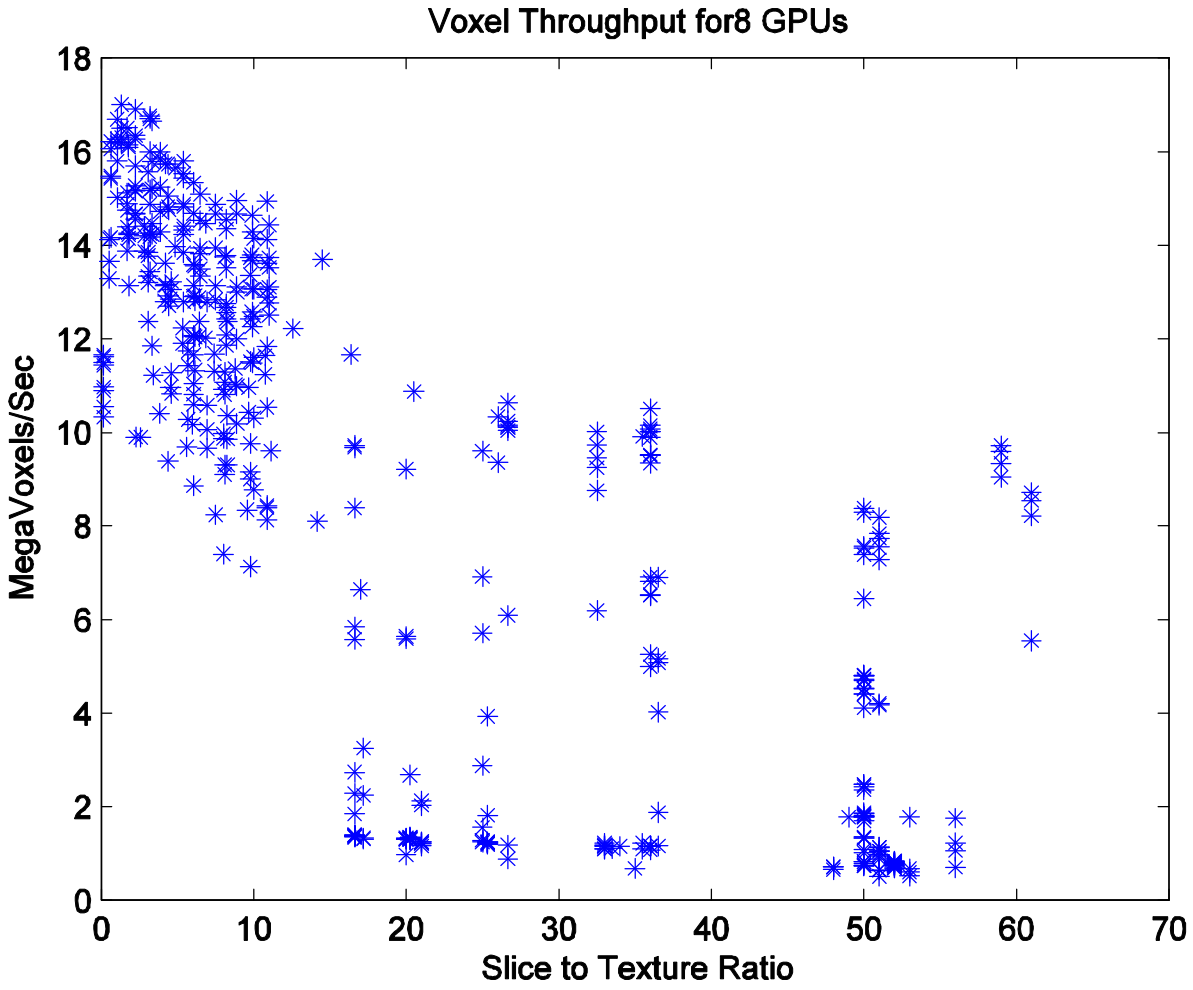

Results: Throughput 1 TV/ 1 GPU

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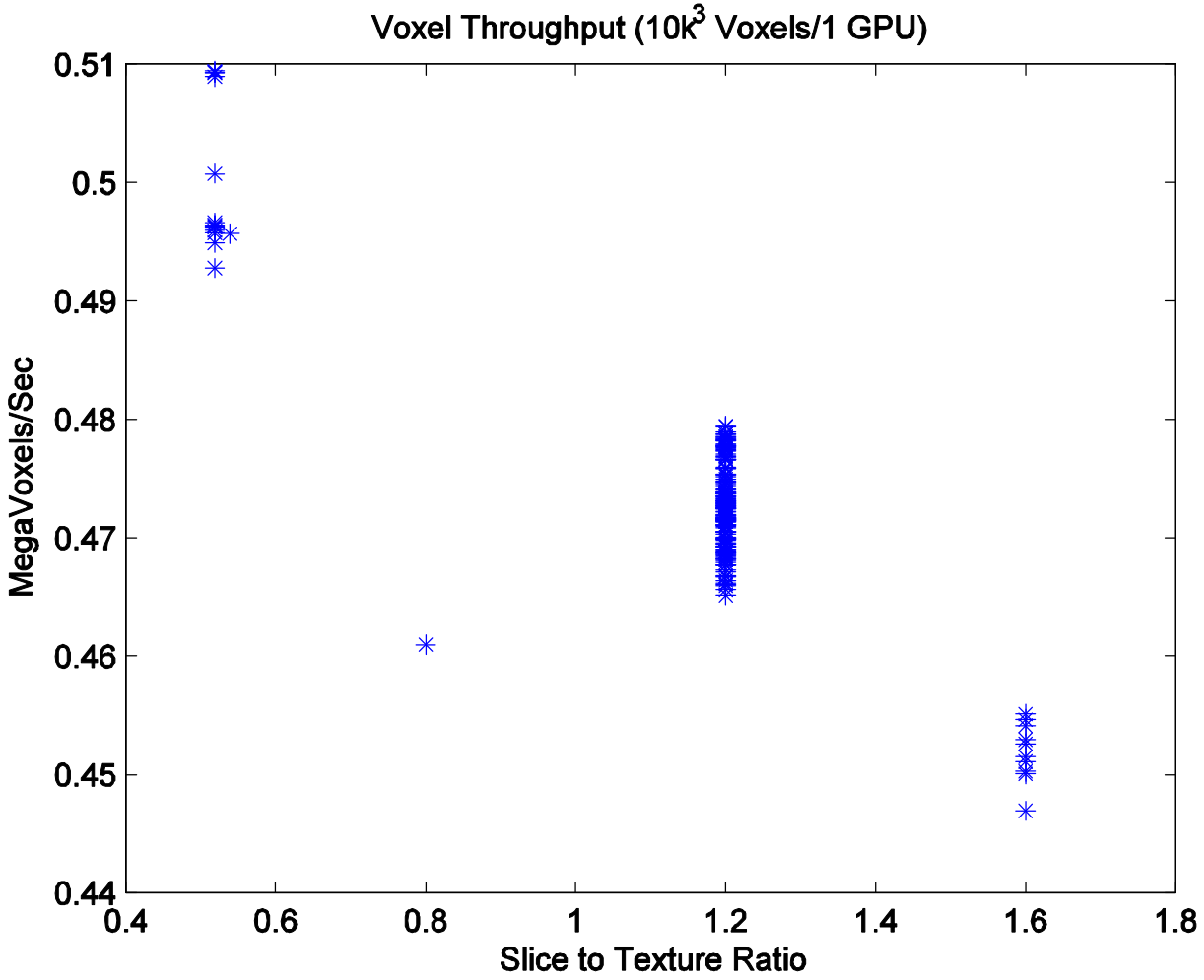

Results: Throughput 1 TV/ 8 GPUs

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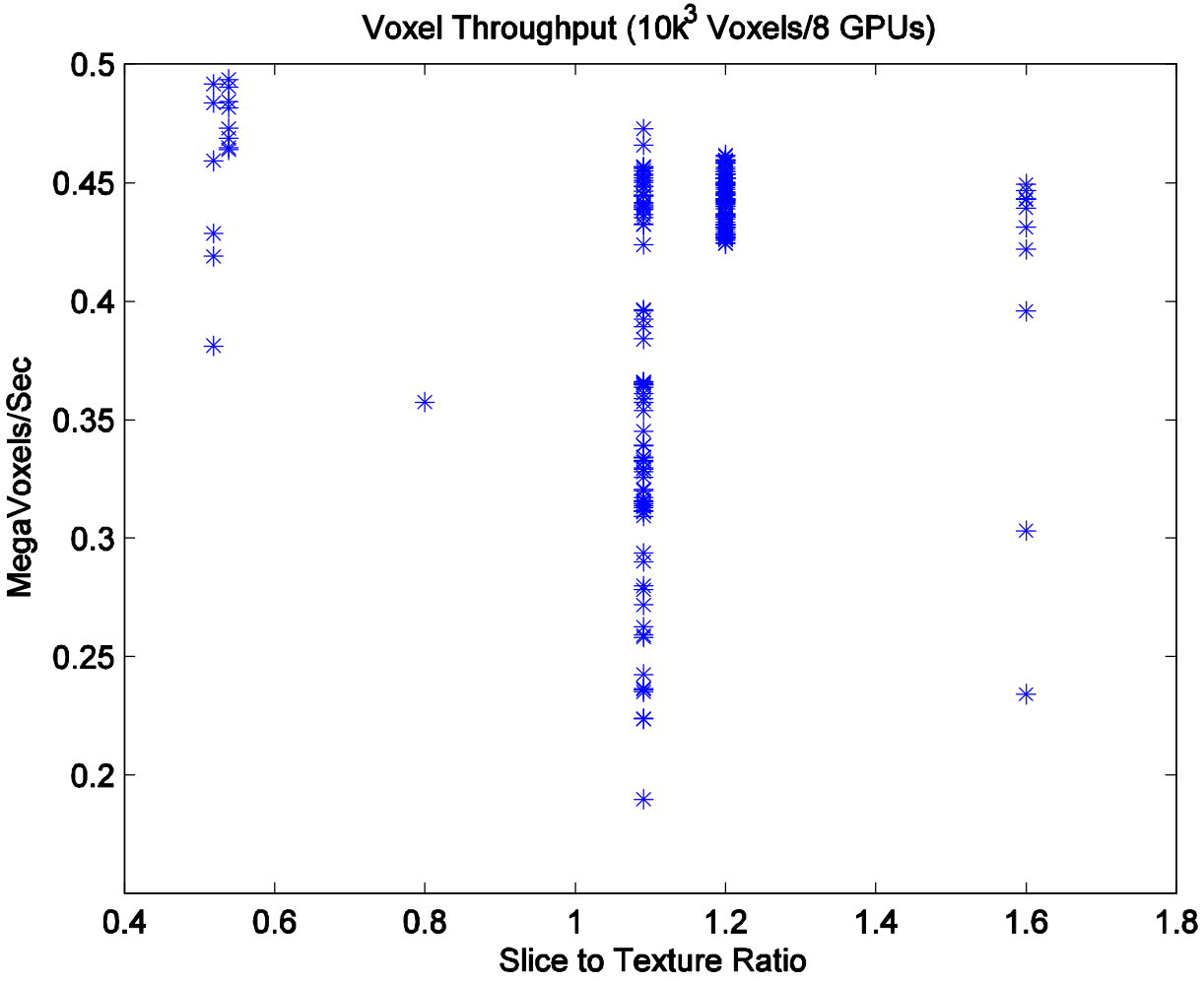

Results: L1 Cache Hit-rates

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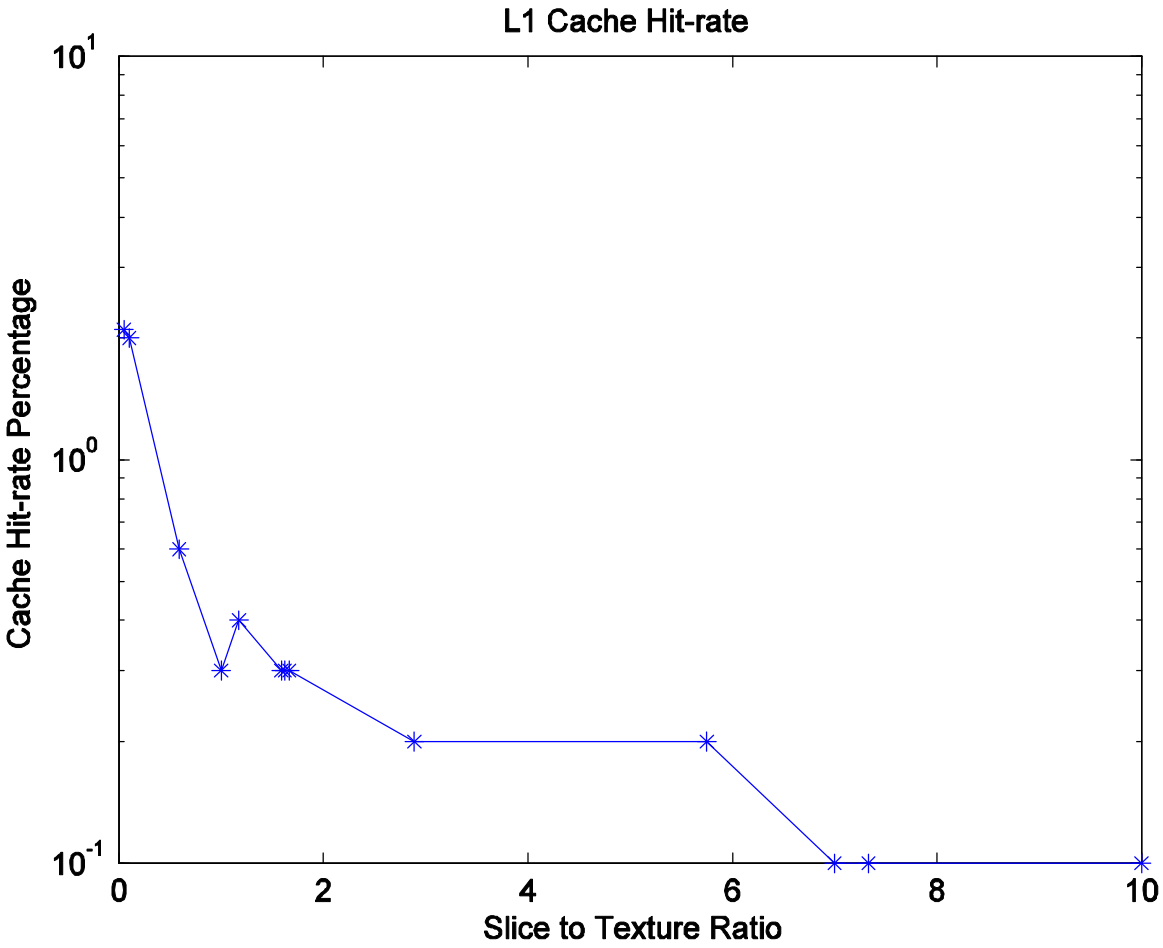
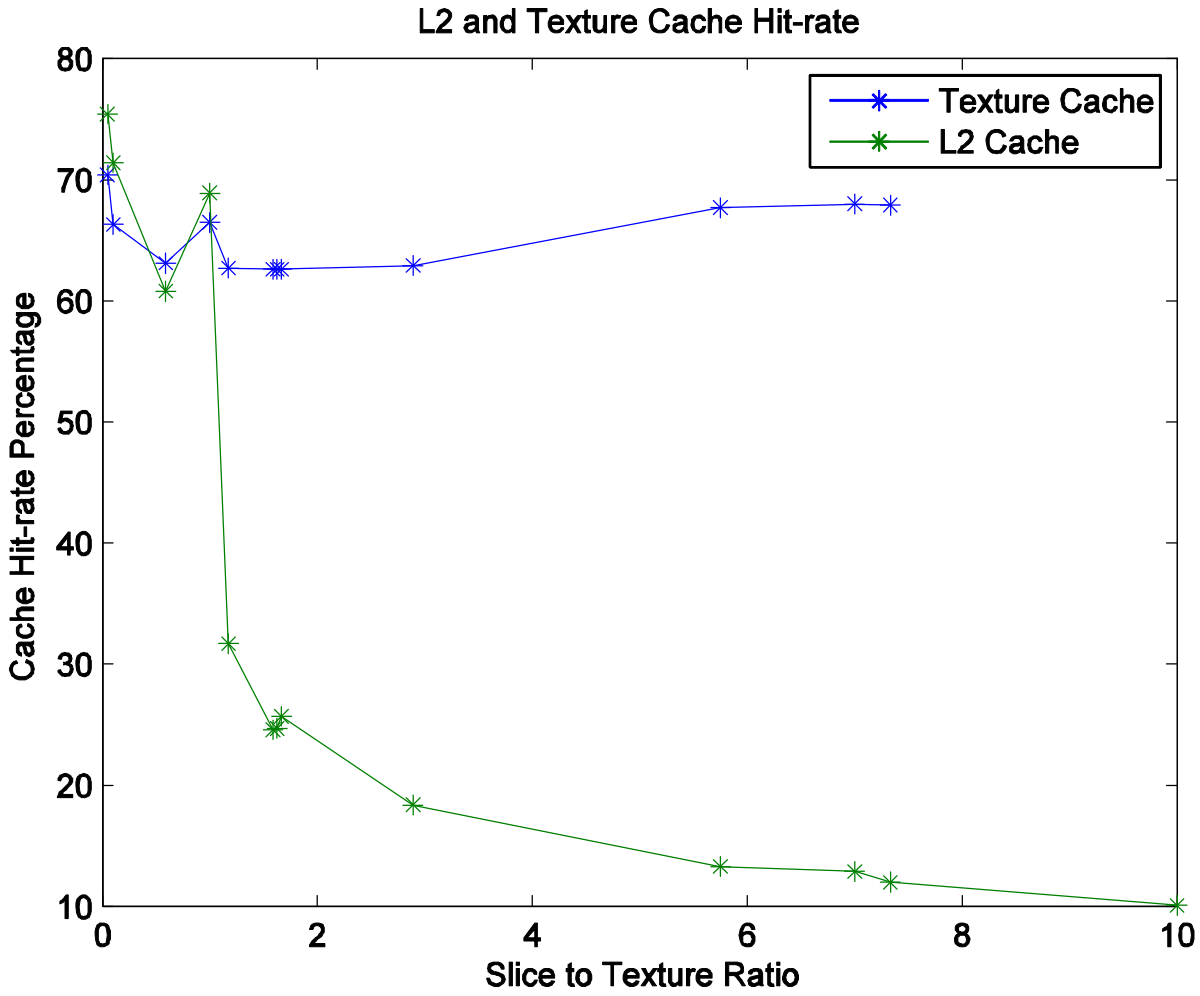


Results: L2 and Texture Cache Hit-rates



Conclusion on Kernel Design

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- Big Data CT Reconstruction kernels clearly benefit from an Irregular approach
  - Massive parallelism has potential to destroy spatial locality
  - Counter Intuitive approach may create performance gains
  - Irregular approach improves voxel throughput by improving cache-hit rates
  - Small X-ray data batches and large subvolume tend to perform best.
- Unfortunately this is only a portion of the problem
- This is a Big Data problem
  - Moving information to and from storage media
  - Host-side data
- Next Problem: Rest of the system cannot keep up.

Big Data CT

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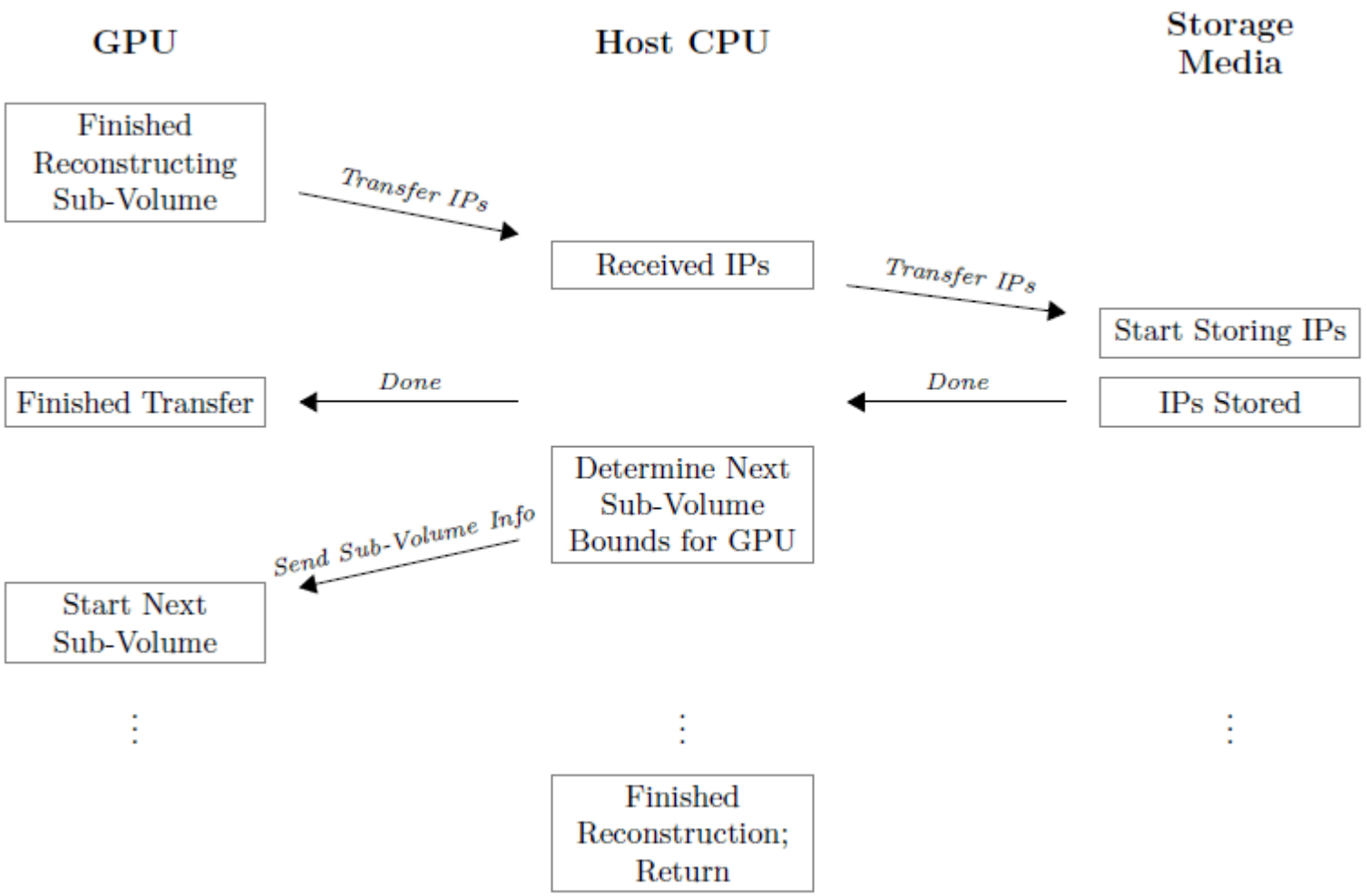
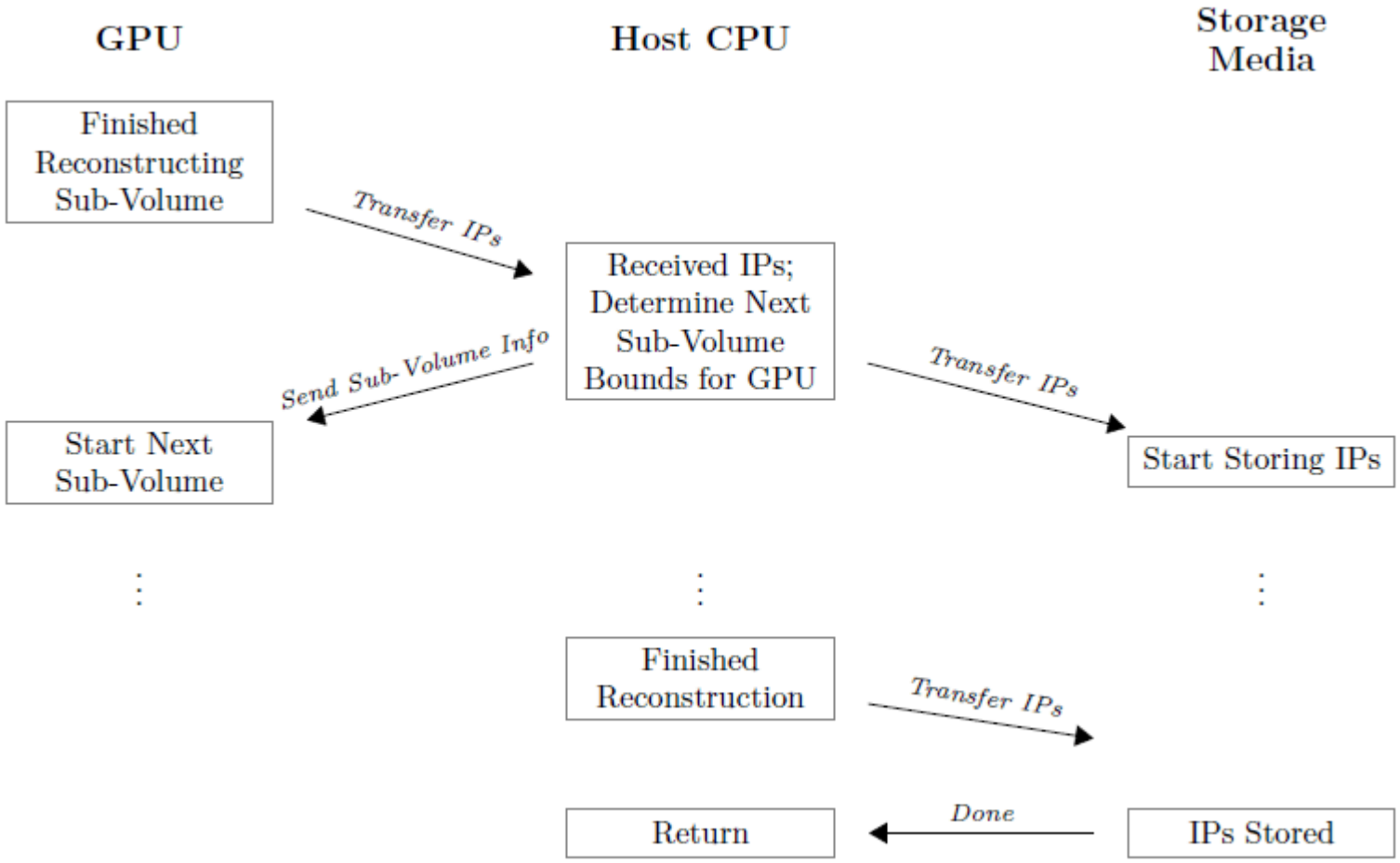
- Industrial-Scale Computed Tomography Datasets
  - Differ from Medicine
  - Medical datasets are typically less than a few gigabytes
  - Industrial scale datasets are dozens of Gigabytes to several Terabytes!
- The reconstruction is large
  - The fastest supercomputers cannot be used due to memory.
  - Waiting days to years is not practical!
  - Suboptimal GPU utilization.
- Industrial-Scale CT is really Big Data CT that impacts many areas.
  - Non-Destructive Testing
  - Materials Characterizations
  - Quality Assurance
  - Verification and Validation

Serial Implementation



Modularization



Results: GPU Speedups

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- Speedup is relative to single thread CPU time of 44,987 hours

Number GPUs	Modular Time	Modular Speedup	Serial Time	Serial Speedup
1	102.7	438x	113.9	395x
2	53.3	844x	59.8	752x
4	30.3	1486x	37.4	1204x
6	23.1	1946x	28.0	1608x
8	19.9	2260x	23.3	1927x

Results: GPU Speedups

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- Speedup is relative to OpenMP CPU time of 4,039 hours

Number GPUs	Modular Time	Modular Speedup	Serial Time	Serial Speedup
1	102.7	39x	113.9	35x
2	53.3	76x	59.8	68x
4	30.3	133x	37.4	108x
6	23.1	175x	28.0	144x
8	19.9	203x	23.3	173x

Overall Improvements

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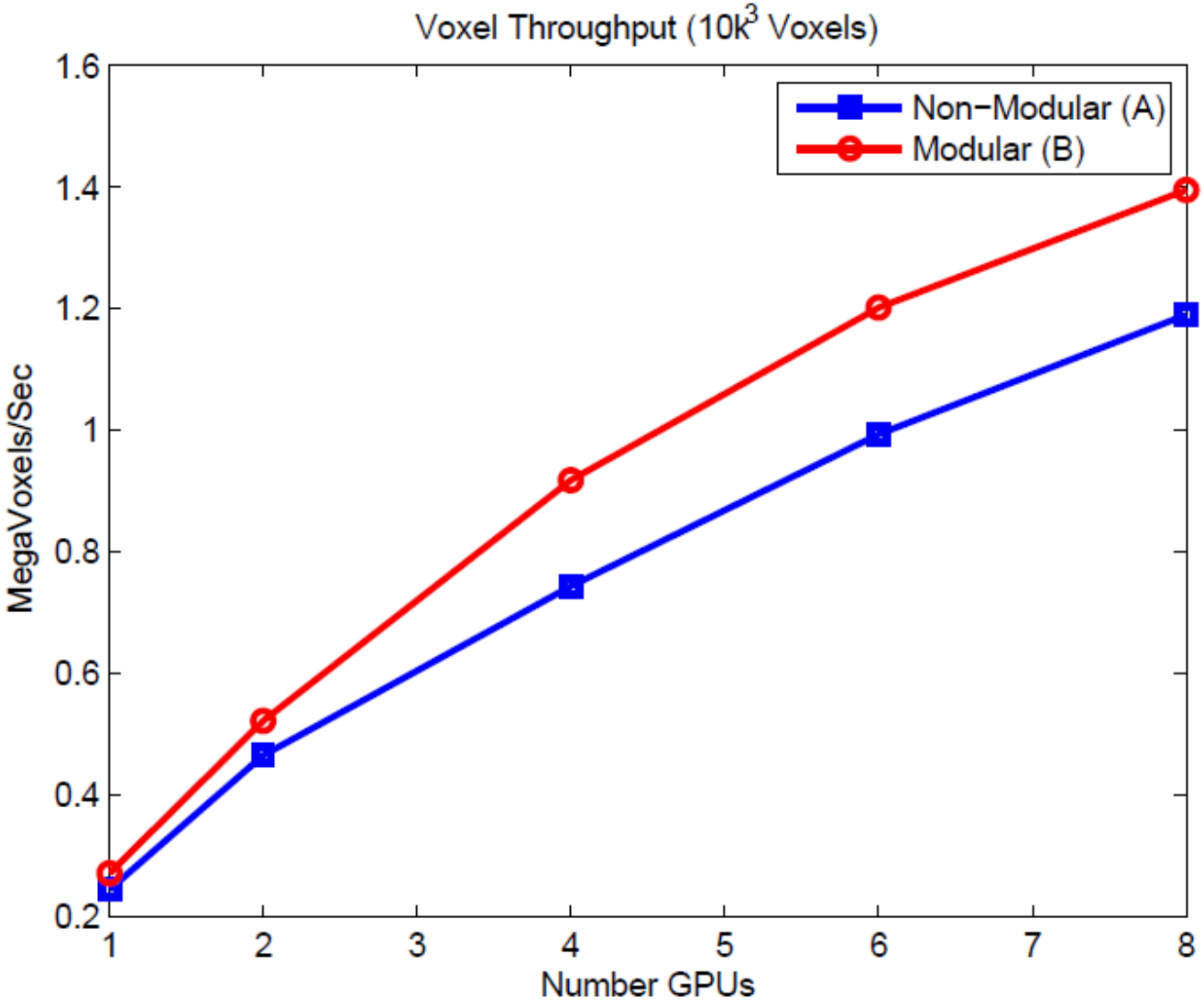

Pulling It All Together

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- GPUs are fast.
  - New Bottlenecks are cropping up.
  - Modularization helps.
- There has been little work in energy efficiency.
  - Are we trading one problem for another?
  - Most facilities have limited energy capacity
- For Big Data, consumption metrics may be unsustainable.
  - Same hindrance as Exascale Computing
- CPU-based vs. GPU-based comparisons
  - Computation times are proven, what about efficiency?
- Serial-based vs. Modularized-based comparisons
  - Does our approach help or hinder consumption?

Energy Efficiency

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- What aspects contribute the most?
  - Data transfer
  - Computation
  - I/O
- Looking at overall energy consumption is insufficient.
  - Does not factor performance.
- Other popular metrics:
  - Performance-per-Watt: Factors in power of the system.
  - Energy-Delay: Greater emphasis on performance.
    - Defined as *KWH*H.*
    - Lower is better.
- Studying a single metric can be misleading!

Overall Energy Consumption

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- Total energy used by an algorithm.
  - Simple metric to grasp.
- Comparison between systems and algorithms is straightforward.
- However, this metric does not factor the time consumed during the computation.
- Identical consumption is possible with dramatically different computation times

Performance-Per-Watt

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- This metric is measured as “million-instructions-per-second-per-watt”.
- Somewhat factors computation time
- This metric is typically used when energy consumption is vital.
  - Systems that run on primarily batteries (e.g. notebooks, tablets, etc.)
- Not sufficient as one could sacrifice speed to increase this metric.

Energy-Delay

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- The Energy-Delay metric is a relatively new metric.
  - Total Energy (KWH) multiplied by computation time.
- Some forms of the energy delay product square or cube the delay when greater emphasis on performance is desired.
- First proposed to evaluate trade-offs between circuit level power savings techniques for digital designs.

Implementation

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- Leveraging pinned host memory minimizes idling between kernel launches applied to a given sub-volume.
- As mentioned, data writing is another source of GPU idle.
  - Ideally, the modularized approach would minimize this idling.
  - Is this savings moot with the complexity of the task on the CPU?
- Both implementations are written in a hybrid environment:
  - C++
  - CUDA (Ver. 5.0)
  - OpenMP

Evaluation

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- Metrics to be measured:
  - Energy Consumption
    - To be measured in kilowatt-hours (kWh).
  - Performance-Per-Watt
    - Presented as voxels-reconstructed (and stored)-per-second-per-watt.
    - Modified from traditional MFLOPS-per-watt
    - Reconstruction is known to be limited in memory bandwidth and computation.
  - Energy-Delay Product
    - To ensure algorithm is not trading off speed for savings.
    - Square weighting of delay as suggested by other works (Laros III et. Al.).

Evaluation Cont.

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- Four CT implementations measured:
  - Popular CPU-based Approach
    - Leverages OpenMP for multi-threading and MPI for parallel processing
  - Naïve GPU Implementation:
    - Baseline
    - No GPU-specific exploitation
    - Brute force Port of CPU-like implementation
    - Up to 8 GPUs
  - Serialized Approach
    - Up to 8 GPUs
  - Modularized Approach
    - Up to 8 GPUs

Evaluation Cont.

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- System used:
  - Supermicro server
    - Dual octo-core Intel Xeon E-2687W @ 3.1GHz w/ Hyper threading
    - 512GB system memory
  - 8 NVidia Tesla M2090 GPUs
    - Contained in 2 NVidia S2090 units
    - Connected via 4 PCI-E 2.0 x16 host interface cards
  - Storage Media
    - 8 x 3TB 6 Gb/s drives in RAID 0
    - Controlled by an Intel Controller with 1 GB of DDR3 cache.
  - Metrics obtained with several P3 International P4460 Kill-A-Watt Monitors
  - GPUs disconnected for CPU measurements

Evaluation Cont.

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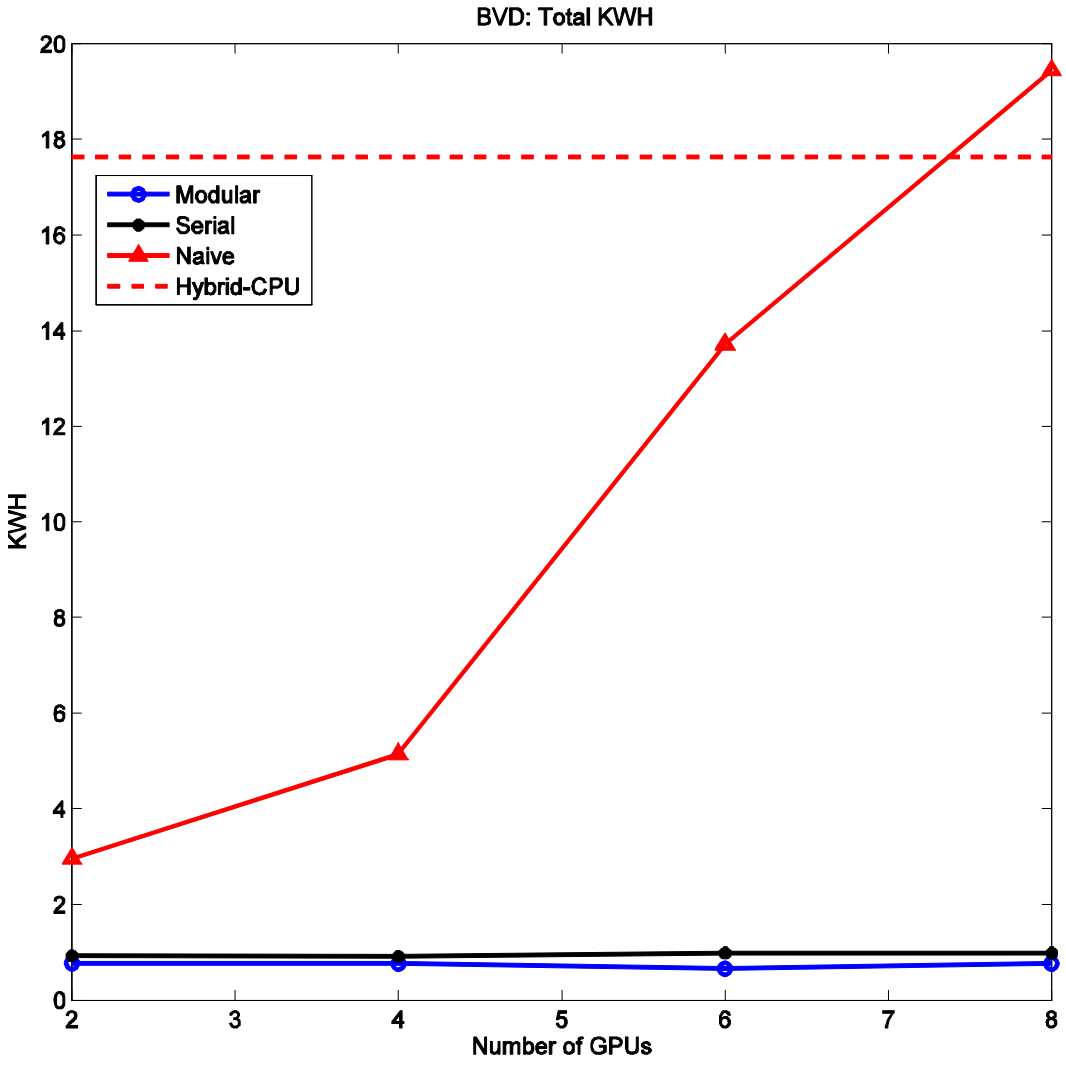
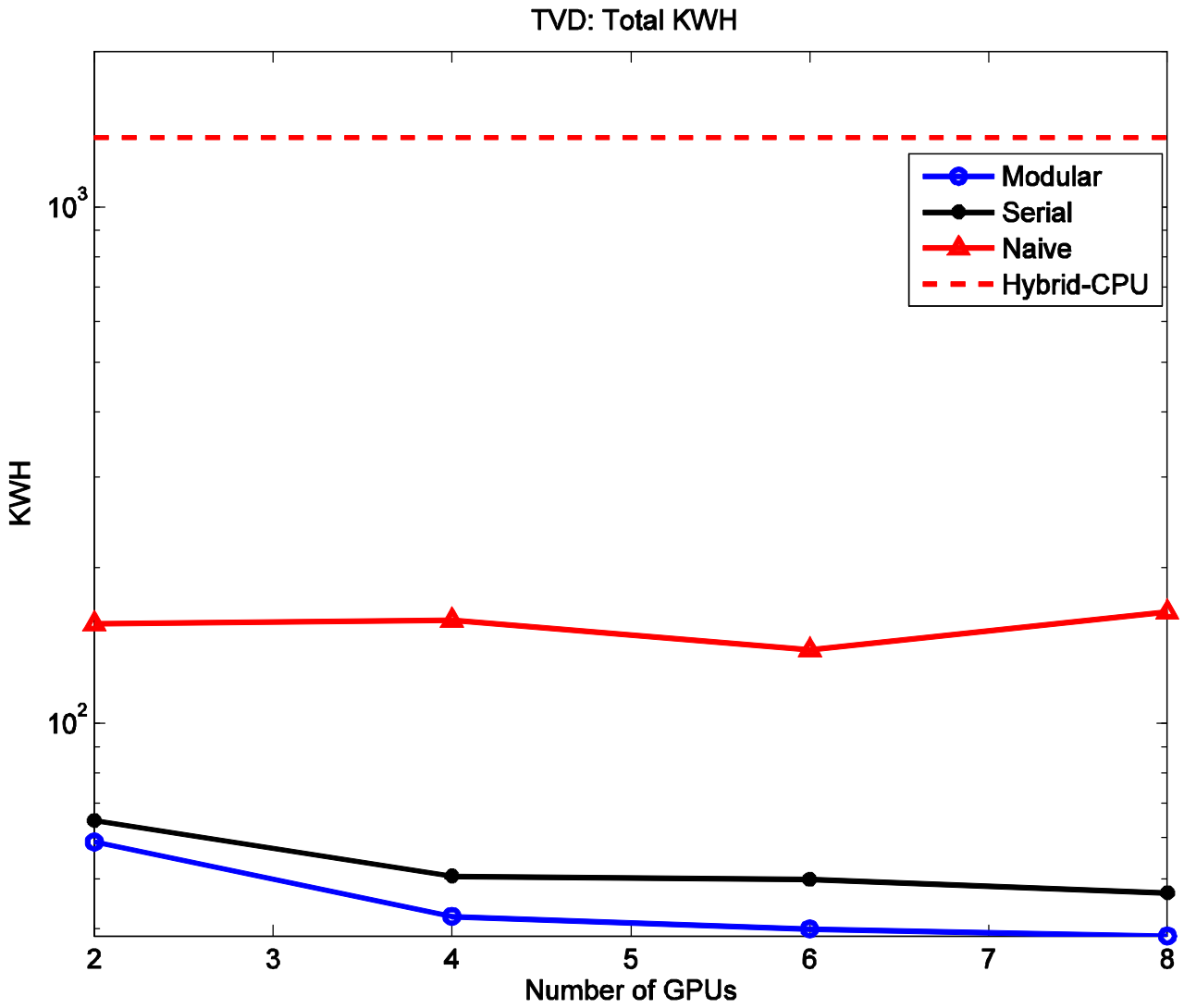
- Two datasets used
- 64 Gigavoxel Reconstruction
  - 4000x4000x4000 voxel volume
  - 1800 Projections
  - High-end of current acquisitions
- 1 Teravoxel Reconstruction
  - 10K x 10K x 10K voxel volume
  - 10,000 Projections
  - “Future-proof” dataset.

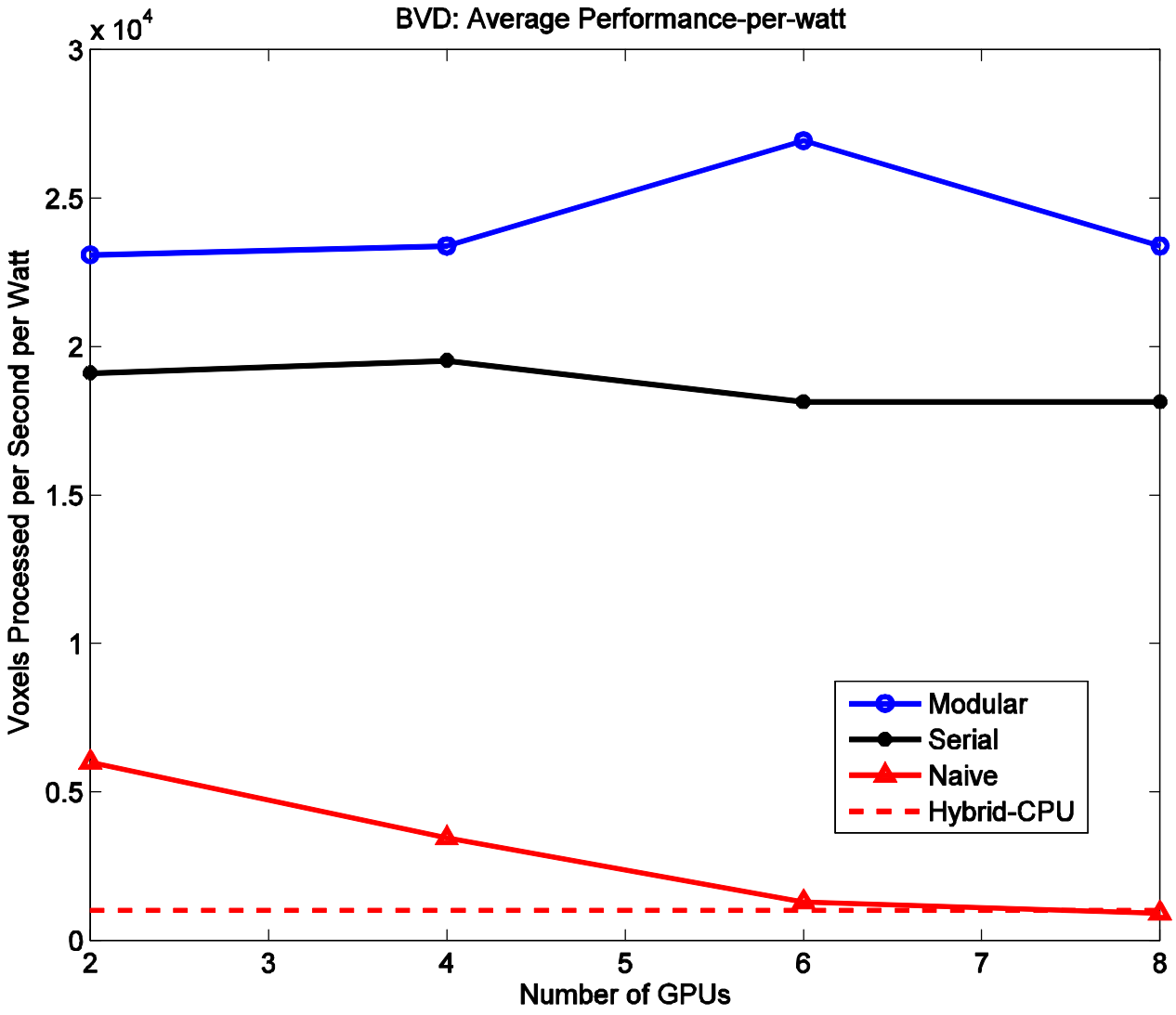
Energy Consumption 64 GV



Energy Consumption 1 TV



Performance-Per-Watt 64 GV



Performance-Per-Watt 1 TV

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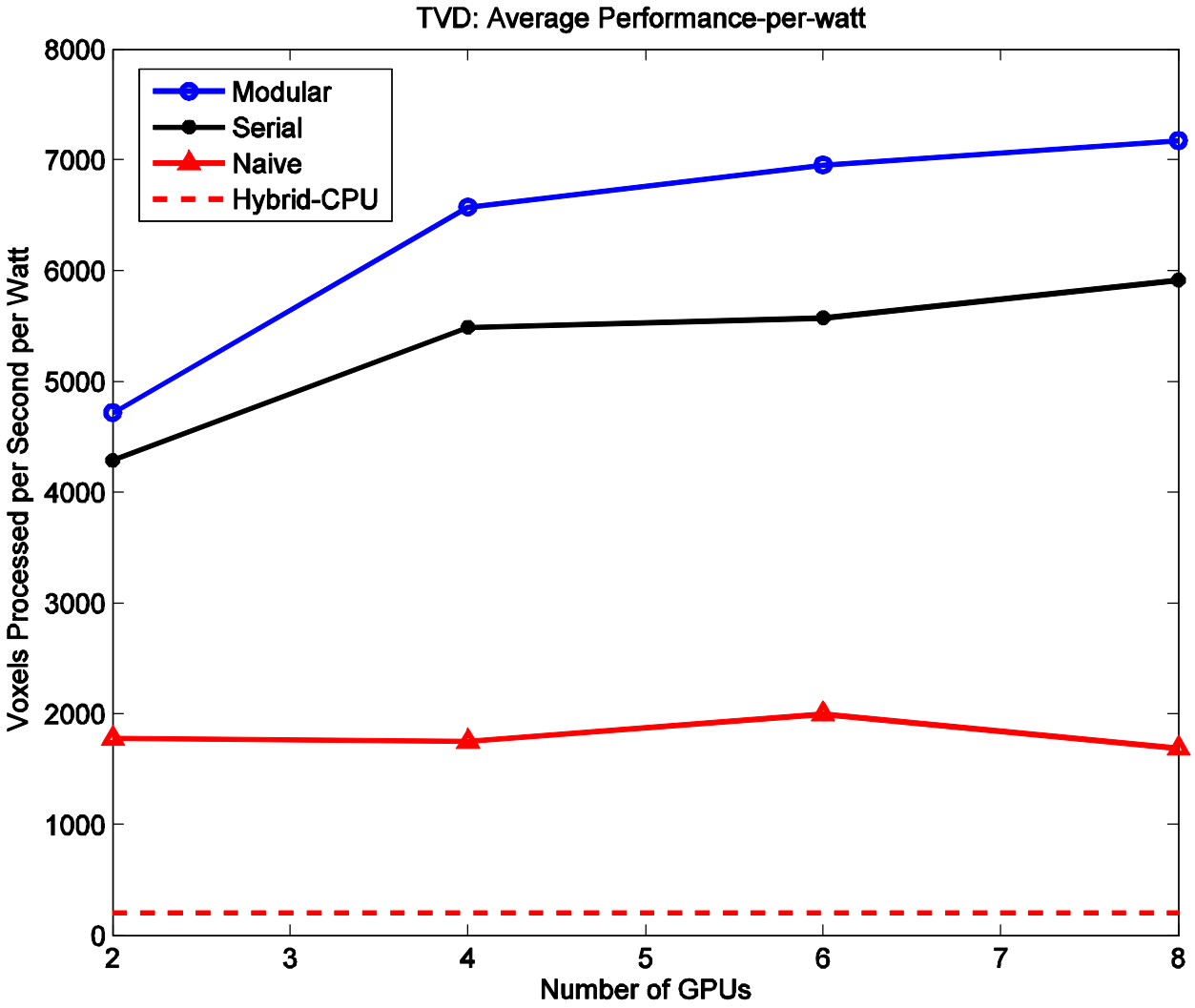
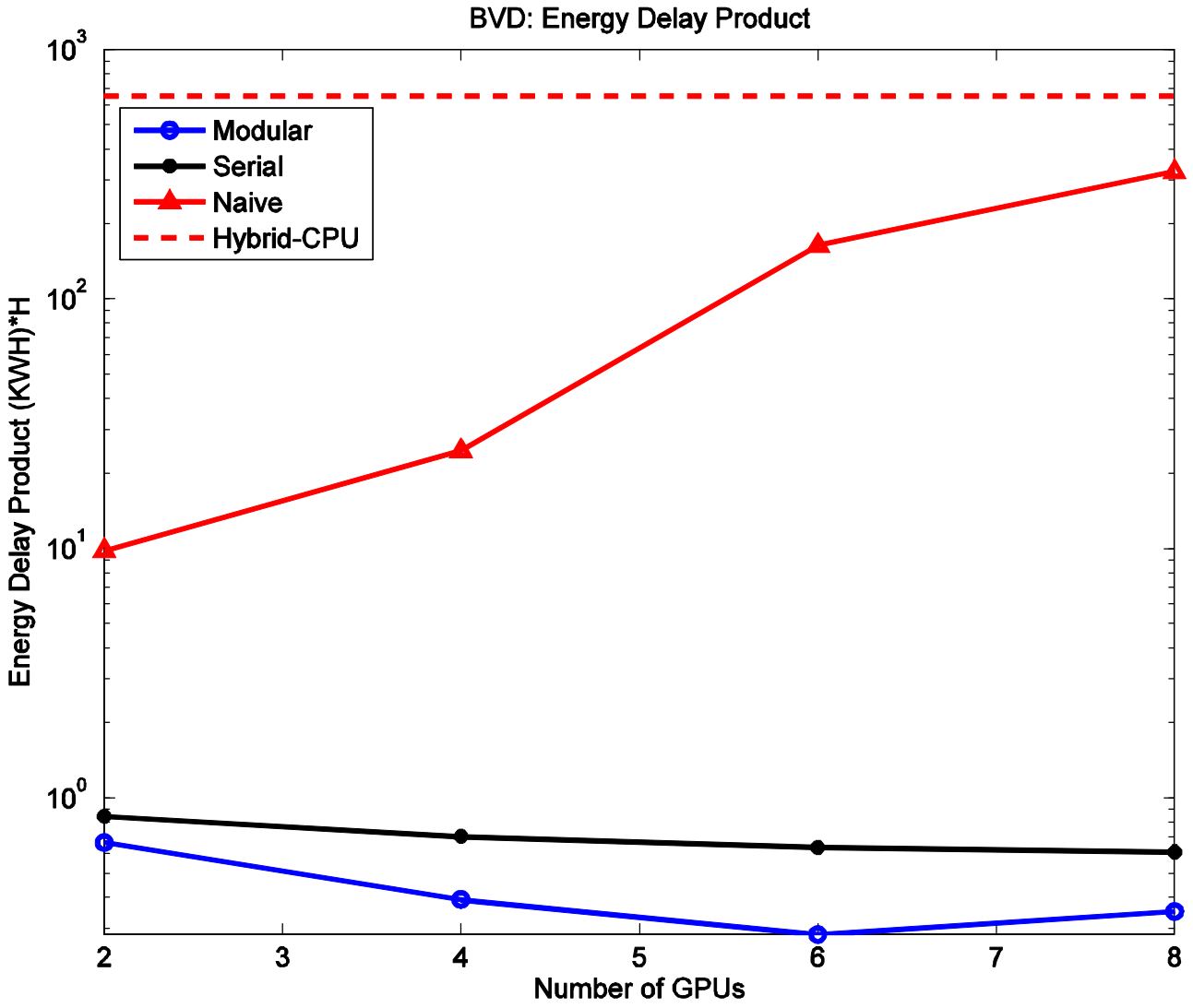
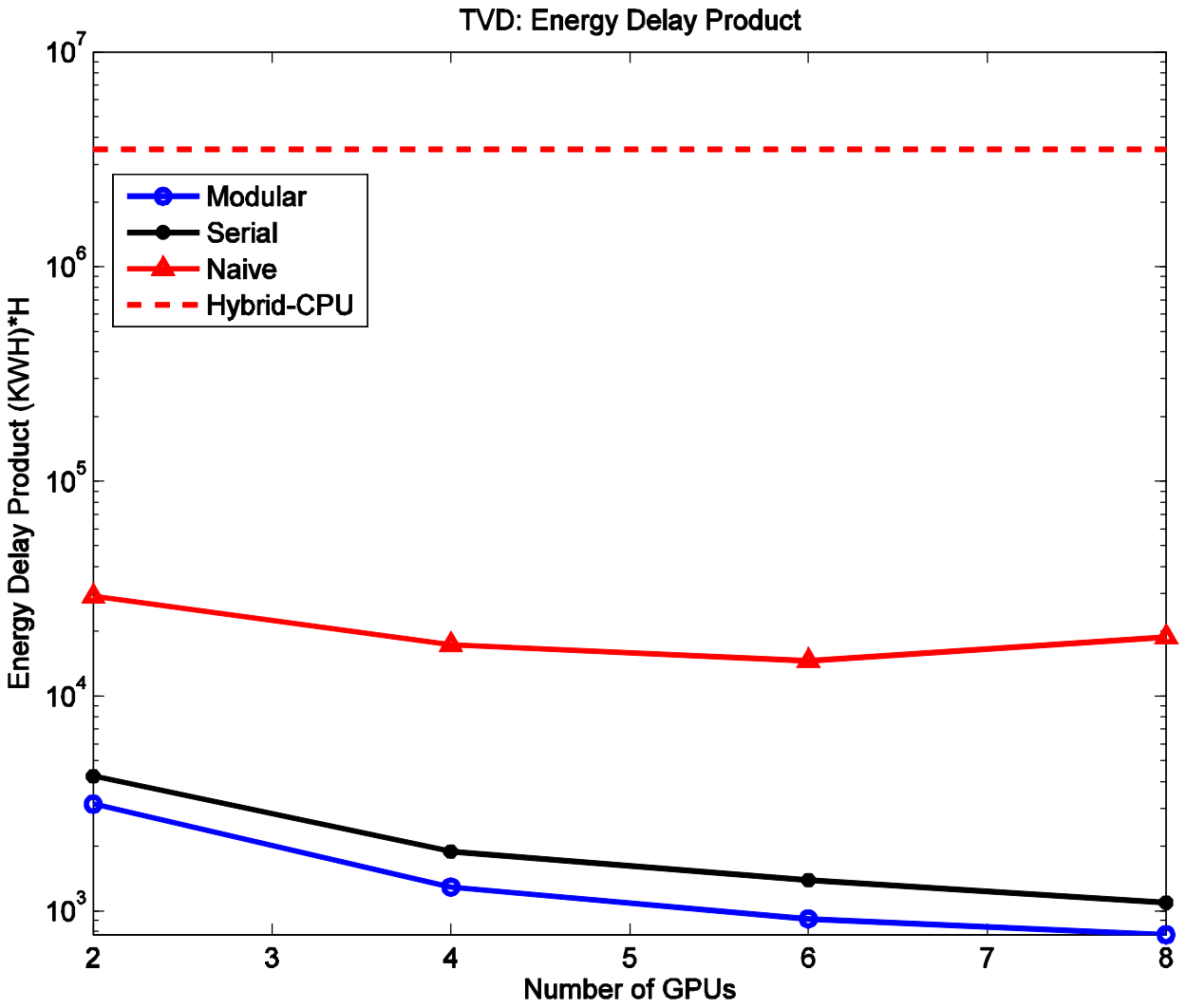


Results: Energy-Delay 64 GV



Results: Energy-Delay 1 TV



Conclusions

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- This work has shown that leveraging GPUs not only improves computation time, but does so while improving multiple energy metrics for FDK reconstruction.
- The computation community is approaching energy limitations, intelligent algorithm design can help.
- Testing a heterogeneous cluster approach with promising results!
- What other algorithms can benefit from this work?